Human Development Disparities and Convergence across Districts of Indonesia: A Spatial Econometric Approach

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A Spatial Econometric Approach

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Abstract Using a novel district-level dataset of the human development index, this paper studies the evolution of regional disparities in Indonesia over the 2010-2018 period. In particular, the paper evaluates the role of spatial dependence on the speed of regional convergence. The main findings are threefold. First, regional disparities have been decreasing in the overall index of human development as well as in most of its components. Second, there are considerable differences in the speed of convergence in the components of the human development index. Specifically, education-related components have tended to accelerate the speed of regional convergence, while life expectancy and expenditure components have tended to decelerate it. Third, there is an increasing degree of spatial dependence that is associated with the decreasing regional disparities. Moreover, results derived from spatial convergence regressions indicate that the performance of neighboring regions has a significant effect on the speed of regional convergence.

Keywords Human development index · Regional inequality · Convergence · Spatial dependence · Indonesia
JEL Classifications R10, O15, R58

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1 Introduction

The concept of human development involves expanding people's freedoms, capabilities, and choices in a sustainable way. The human development index (HDI) was formulated by the United Nations in 1990 as a composite index for evaluating long-run achievement on three fundamental key aspects of human development: long life, education attainment and knowledge access, and decent standard of living (Anand and Sen 2000). According to this index, the performance of Indonesia has been lagging behind. In 2019, UNDP reports Indonesia ranked 111 out of 189 countries. Moreover, large regional disparities threat both the achievement and sustainability of the development agenda put forward by the United Nations in the declaration of the sustainability development goals (SDGs).

Motivated by the negative effects of regional inequality on sustainable development, this paper studies the evolution of regional disparities in the human development index, and its components, across 514 districts of Indonesia over the 2010-2018 period. In particular, this paper evaluates the role of spatial dependence on the evolution of regional disparities and the speed of regional convergence. The insular geography of Indonesia and its largely unbalanced geographic distribution of natural resources and population provide a unique setting for evaluating the role of spatial inequality on sustainable development. To achieve this objective, this paper uses both exploratory spatial analysis methods and spatial convergence regressions.

There is a large and growing literature on regional inequality and convergence in Indonesia. Starting from the seminal contributions of Esmara (1975); Akita (1988); Garcia and Soelistianingsih (1998) to the recent papers of Kataoka (2019); Kurniawan et al (2019); Mendez (2020), many studies have used province-level data to draw inferences on the evolution of regional disparities. Few studies, however, have used district-level data to evaluate the role of geographical neighbors on regional disparities. Among those few studies, the work of Vidyattama (2013) and Vidyattama (2014) apply spatial convergence regressions to examine whether the performance of neighbouring districts can determine the speed of regional convergence. Based on district-level data for the 1999-2008 period, the results Vidyattama (2013) indicate that regional convergence in human development is taking place, but the performance of neighboring regions has a minimal effect on the speed of regional convergence.

The main findings of present paper aim to contribute to the literature on regional disparities and convergence in Indonesia in three fronts. First, using the latest district-level data available for the 2010-2018 period, this paper confirms that regional convergence in human development is taking place in Indonesia. Second, the paper documents considerable differences in the speed of convergence across the components of the human development index. Specifically, expected years of schooling and mean years of schooling have tended to accelerate the speed of convergence of human development, while expenditure per capita and life expectancy have tended to decelerate it. Third, it shows that increasing spatial dependence is associated with decreasing regional disparities. Moreover, based on this new dataset, the performance of neighboring regions has a larger effect on the speed of regional convergence than that reported in the previous studies.

The rest of this paper is organized as follows. Section 2 provides an overview of the related literature on regional disparities and convergence. Section 3 describes the methods and data. Section 4 presents the results, and Section 5 offers some concluding remarks.

2 Related literature

2.1 Regional disparities in Indonesia

Many studies have documented the large regional disparities across regions in Indonesia. Among the first contributions of regional disparity studies in Indonesia, Esmara (1975), Uppal and Handoko (1986) have examined wide disparity among the provinces of Indonesia in average income. It has revealed that the highest average income generated from the capital city of Indonesia, Jakarta, in Java Island, and the resource-rich provinces, which are, mostly in Sumatra islands. The lowest average income was the Java islands and the East part, respectively.

In addition, provincial level studies show large disparities among provinces in Indonesia. For instance, Akita (1988) finds that economic structures and economic opportunities are unevenly distributed among the five main islands of Indonesia. This uneven distribution becomes more obvious in the Java island, which generates almost 60 percent of the Gross National Domestic Product if the mining sector is excluded from the computation. Akita and Lukman (1995) evaluates regional disparities across regions in Indonesia using the Williamson Index, a measure of the coefficient of variation is used to analyze changes in regional disparities at the provincial level over the 1975-1992 period. The result indicates a large decrease in GRDP per capita disparities among provinces.

Moving to a different level of observation, Tadjoeddin et al (2001) shows that regional disparities in Indonesia are stable at the district level by examining the Theil and Gini coefficients of GRDP per capita from 1993 to 1998. Akita (2002) finds similar results at the district level, claiming that regional disparities in terms of income increased over the 1993-1997. Similarly, Hill et al (2008) finds that regional disparities remained relatively unchanged during 1993-1998 period. In addition, disparities of GRDP per capita with exclusion of oil and gas sector, kept increasing slightly at the district level until 1998.

Using a longer time horizon, over 1983-2004, Akita et al (2011) examines the inter-provincial regional disparities in income. Their results indicate large regional gaps among Indonesia's main islands (Java, Sumatra, Kalimantan, Sulawesi, Papua and Maluku). Moreover, disparities do not only take place within islands, but also among districts within provinces in those islands. Recent studies in Indonesia have been conducted by examining regional disparities across provinces beyond the dynamics of the average province. Using a hierarchical decomposition analysis over the 1996-2010 period, Akita and Miyata (2018) find that some spatial inequalities are inevitable, given unequal resource endowments, infrastructure and geographical landscape. They also emphasize that disparities between districts within provinces appear to play a significant role in both rural and urban areas, although the gap between major islands is trivial.

2.2 Regional convergence and spatial effects

The empirical analysis of regional convergence is a central topic in regional economics (Magrini 2004). Based on the convergence predictions of the neoclassical growth model (Solow 1956), the seminal contributions of Barro and Sala-I-Martin (1991), Barro and Sala-I-Martin (1992), Sala-I-Martin (1996a), and Sala-I-Martin (1996b) show that across states in the US, prefectures in Japan, and subnational regions in Europe, there is a process of unconditional economic convergence. Specifically, they show that initially poor regions are growing faster than initially rich regions. They also compute the speed of regional convergence and show that convergence is occurring at a rate of 2 percent per year in all these cases. Such speed of convergence would imply that regional disparities could be halved in about 35 years.

Based on the convergence equation proposed by Barro and Sala-I-Martin (1992), many studies have evaluated the convergence hypothesis across countries, industries, and subnational regions.[1] Many studies have studied convergence in variables other than GDP per capita. In particular, in the context of the human development index (HDI), Yang et al (2016) show that there is a weak process of regional convergence across provinces in China over the 1997-2006 period. Marchante and Ortega (2006) compare the convergence dynamics of GDP per capita and various measures of the human development index across Spanish regions over the 1980-2001 period. They find that although regional disparities in GDP have remained constant, there is a process of regional convergence in multiple version of the human development index. Across metropolitan regions in Bolivia over the 1992-2013 period, Mendez (2018) finds a process of regional convergence in human development. Moreover, that process tends to accelerate when the national economy enters a faster economic growth regime.

Since the late 1990s, there has been a growing interest in evaluating how the performance of regional neighbors and their spatial spillovers can alter the rate of convergence of the entire regional system. The seminal contributions in this this line of research are Rey and Montouri (1999) and Fingleton (1999). In the context of regional income differences in the US, Rey and Montouri (1999) first show strong patterns of spatial dependence throughout the 1929-1994 period. Then, they apply spatial econometric methods to show that the convergence equation proposed by Barro and Sala-I-Martin (1992) and Baumol (1986) is misspecified due to ignored spatial error dependence. This type of spatial dependence implies that shocks originating in one state can spillover into surrounding states, potentially complicating the convergence dynamics of the regional system. In the context of regional income differences across subnational regions in the European Union, Fingleton (1999) uses a spatially autocorrelated error model to refine the convergence framework of Barro and Sala-I-Martin (1992). After this adjustment, he finds weak evidence of economic convergence, requiring more than two centuries for convergence to be achieved.

[1] See Abreu et al (2005b); Islam (2003); Magrini (2004) for comprehensive surveys of the findings of these studies.

The spatial convergence approach of Rey and Montouri (1999) and Fingleton (1999) encouraged a large number of studies to evaluate the role of spatial effects in the regional convergence process.[2] For instance, Magalhães and Hewings (2005) study the role of spatial dependence in regional convergence in Brazil. Similar to Rey and Montouri (1999), they find that the classical convergence model of Barro and Sala-I-Martin (1992) is misspecified due to ignored spatial error dependence. Although there are some weak patterns of convergence across states, it seems to be more of a regional phenomenon than a global convergence process. More recent studies from Brazil (Cravo et al 2015; Lima and Silveira Neto 2016; Resende et al 2016) are consistent with those findings and support the existence of neighbour effects in the process of convergence.

There are also several recent studies about spatial regional convergence in Europe. For instance, Di Liberto (2008) shows that in Italy, regions are benefiting from spatial spillovers of higher levels of education. Other studies have also reported regional spillovers in human capital (Rauch 1993; Fingleton and López-Bazo 2006; Rosenthal and Strange 2008). Pietrzykowski (2019) shows a high degree of spatial dependence across the subnational regions of Europe. This study also shows that both the spatial lag and spatial error models increase the fit of the convergence model and national effects are important for the convergence process of Europe. Kubis and Schneider (2012) use a conditional convergence approach and panel data estimation methods to show that neglecting the spatial dimension under-estimates the speed of convergence across German regions over the 1993-2008 period. Kubis and Schneider (2012) also point out that further research is needed when using panel data with short time horizons. Specifically, short panels tend to have too much noise and could be affected by fluctuations in the busyness cycle. Barro (2015) is even more skeptical about the use of short panels. Using various simulations, he shows that short panels tend to over-estimate the speed of convergence.

2.3 Regional convergence in Indonesia

There is a growing literature about regional convergence in Indonesia. The majority of the studies have used provincial level datasets to study regional

[2] See Abreu et al (2005a), Le-Gallo and Fingleton (2019) and Rey and Le-Gallo (2009) for surveys of the spatial convergence literature.

income convergence. Garcia and Soelistianingsih (1998) are the first authors to study regional convergence based on the classical convergence framework of Barro and Sala-I-Martin (1992). They provide evidence in favor of provincial convergence at a rate of two percent per year over the 1975-1983 period. Resosudarmo and Vidyattama (2006) use panel data methods and a conditional convergence framework to study the income disparities across 26 provinces over the 1993-2002 period.[3] They find that initially poor provinces have grown faster that initially rich provinces. Although Resosudarmo and Vidyattama (2006) do not report the speed of provincial convergence, their estimated convergence coefficient largely changes from –0.02 to -0.59 when panel fixed effects are used. This large change illustrates the argument of Barro (2015) in the sense that short panel fixed effects can lead to misleading values of the speed of convergence.[4] Hill et al (2008) show that the speed of regional income convergence is both unstable over time and sensitive to the performance resource-rich provinces.

More recent studies have used alternative convergence frameworks that emphasize the role of regional heterogeneity and convergence clubs. For instance, Kurniawan et al (2019) finds that the provinces of Indonesia are characterized by multiple convergence clubs in welfare-related variables. Similarly, Mendez and Kataoka (2020) and Mendez (2020) find multiple convergence clubs in productivity-related variables. Using district-level data, Aginta et al (2020) identify the formation of five convergence clubs across 514 districts over the 2000-2017 period. Although the club convergence approach used these studies provides new insights about heterogeneous patterns of convergence, it does not provide an evaluation of the role of spatial dependence in the convergence process.

There are relative few studies that evaluate the role of spatial effects on the process of regional convergence. Vidyattama (2013) uses the spatial version

[3] In this case of the conditional convergence framework, the following variables were used as controls: an index of foreign direct investment, the gini coefficient, an index of trade openness, local government investments, the share of gas and oil in GDP, financial institution development, and the typical variables of the augmented Solow growth model (Mankiw et al 1992). Due to large differences in institutions and technologies, a conditional convergence analysis is highly recommended to study disparities across countries (Barro and Sala-I-Martin 1992; Barro 2015). In contrast, within countries, an unconditional approach is usually implemented as such differences are smaller and factors of production can move without restrictions across subnational regions (Barro and Sala-I-Martin 1992; Abreu et al 2005a; Magrini 2004; Rey and Montouri 1999; Magalhães and Hewings 2005).

[4] In defense of Resosudarmo and Vidyattama (2006), they acknowledge the limitation of using panel fixed effects with a short time spam (10 years).

of the convergence framework of Barro and Sala-I-Martin (1992) to evaluate whether the performance of neighboring regions (provinces and districts) affects the speed of regional convergence. His main results are three-fold. Over the 1999-2008 period, the process of per-capita GDP convergence is not statistically significant. In contrast, regional convergence in the human development index is statistically significant. The effect of neighbors is statistically significant in both variables, but they have little effect on the speed of convergence. Gunawan et al (2019) use a spatial-filtering approach to study the dynamics of the income distribution across districts over the 2000-2017 period. Their results show that the performance of regional neighbors has played a role in reducing regional polarization in Indonesia.

3 Methodology and data

3.1 Exploratory spatial analysis methods

As argued by Anselin et al (2007), exploratory spatial data analysis (ESDA) methods are useful for discovering, organizing, and monitoring patterns that vary across space. Spatial dependence methods, in particular, can extract valuable information from a dataset by integrating the notion of attribute similarity with locational similarity. The spatial exploration usually starts with an analysis of global spatial dependence. Its main purpose is to test for the existence of an overall pattern of clustering in the spatial distribution. If the null hypothesis of spatial randomness is rejected, then the spatial ordering of the data provides additional information about the phenomenon under study.

There are several statistical tests to evaluate the existence of spatial dependence in a dataset. Among them, the Moran's I test is the most popular. Formally, this test can be defined as:

$$I_x = \sum_i \sum_j w_{ij} \cdot (x_i - \mu) \cdot (x_j - \mu) \; / \sum_i (x_i - \mu)^2 \qquad (1)$$

where w_{ij} represents the spatial structure of the data, and it is constructed from a spatial weights matrix (see Section 3.3 for details), x_i is the value of the variable x at location i, x_j is the value of the same variable at location j, and μ is the cross-sectional mean of the data. Statistical inference for Moran's I can be implemented using either an assumption of normality or a simulation of a reference distribution based on random permutation (Anselin 1995).

A local analysis of spatial dependence complements the analysis of global dependence by identifying the specific location of spatial clusters and outliers. Specifically, local spatial patterns such as hot spots (relatively high values), cold spots (relatively low values), and spatial outliers (high values surrounded by low values and vice-versa) can be identified using the methods development by Anselin (1995). The local version of the Moran's I can be computed for each spatial unit and it is defined as:

$$I_i = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{ij} \cdot (x_j - \mu) \tag{2}$$

where the notation follows that of Equation 1. Statistical inference is based on a conditional permutation approach. One of the most appealing features of an analysis of local spatial dependence is that statistically significant values can be plotted in a map. Thus, it greatly facilitates the spatial identification of high and low value clusters (hotspots and coldspots) and spatial outliers.

3.2 Regional convergence and spatial models

Based on the classical unconditional convergence framework of Barro and Sala-I-Martin (1992), the speed of regional convergence (β) is usually computed through the estimation of the following regression model:

$$log\left(\frac{y_{i,t+T}}{y_{it}}\right) = \gamma - \left(1 - e^{-\beta T}\right) log\, y_{it} + \varepsilon_i, \tag{3}$$

where y_{it} is the value of the variable under study at time t, T is the length of the observation interval, γ is a constant term, and ε_i is a random error. As in most of the regional convergence literature, the estimation of Equation 3 is carried out by the method of ordinary least squares (OLS) using cross-sectional data (Abreu et al 2005a; Magrini 2004).[5]

Based on the speed of convergence (β), a second parameter of interest can be computed as

$$half\text{-}life = \frac{log2}{\beta}. \tag{4}$$

[5] In order to control for unobserved heterogeneity, Equation 3 could also be estimated using panel data methods (Caselli et al 1996; Islam 1995; Kubis and Schneider 2012). However, as argued by Barro (2015), panel data estimates of the convergence rate can be misleading when the time horizon is short.

This complementary measure of convergence is a ”half-life” indicator. It indicates the time that is needed to halve the distance between an initial position and a long-run equilibrium.

The seminal contributions of Rey and Montouri (1999) and Fingleton (1999) extend the model of Equation 3 to account for the role of spatial dependence across regional units. The motivation for this extension is simple and intuitive: interactions among geographical neighbors can affect the speed of convergence of the entire regional system. If those interactions are not accounted in Equation 3, and they are reflected as spatial dependence in the error term, then the estimates of Equation 3 can be misleading. Unaccounted spatial dependence can lead to biased or inefficient estimates of the convergence indicators.

Econometrically, spatial dependence can be included in Equation 3 through multiple specifications. Based on survey article of Abreu et al (2005a), two most popular specifications used in the regional convergence literature are the spatial lag model (SLM) and the spatial error model (SEM). In the SLM specification, spatial dependence represents the actual interaction among spatial units occurs through the dependent variable. In this context, Equation 3 can be restated as

$$\ln\left(\frac{y_{i,t+T}}{y_{it}}\right) = \gamma - \left(1 - e^{-\beta T}\right)\, log\, y_{it} + \rho \mathbf{W} \ln\left(\frac{y_{i,t+T}}{y_{it}}\right) + \varepsilon_i, \tag{5}$$

where $\mathbf{W}$ is the spatial weights matrix that represents the spatial structure of the data, $\mathbf{W}\ln\left(y_{i,t+T}/y_{it}\right)$ is the spatial lag of the dependent variable, and ρ is a spatial lag coefficient.

In the SEM specification, spatial dependence could represent a missing variable that embodies a spatial structure. In this context, Equation 3 can be restated as

$$\ln\left(\frac{y_{i,t+T}}{y_{it}}\right) = \gamma - \left(1 - e^{-\beta T}\right)\, log\, y_{it} + (\mathbf{I} - \lambda \mathbf{W})^{-1}\varepsilon_i, \tag{6}$$

where $\mathbf{I}$ is a vector of ones, $\mathbf{W}$ is the spatial weights matrix, and λ is a spatial error coefficient.

Both spatial models are estimated through maximum likelihood methods. To choose the best specification, the Akaike information criterion (AIC) as well as the Bayesian Information Criterion (BIC) are implemented. Based on these criteria, the model with lowest value of AIC and BIC is selected. Finally, when the SLM model is selected, the decomposition suggested by LeSage and Pace (2009) is implemented to interpret the direct and indirect (spatial spillovers) effects of the convergence coefficient.

3.3 Data and spatial weights matrix

Regional disparities in human development are measured through human development index (HDI) across 514 districts and over the 2010-2018 period. The human development index, originally formulated and calculated by the United Nations Development Program (UNDP), encompasses three dimensions: health, education, and decent standard of living. The government of Indonesia has followed the three dimensions of the HDI to track the development performance of its 514 districts. Initially, the three dimensions of the HDI were measured as follows. The health dimension was represented by a indicator of life expectancy. The education dimension was represented by two indicators: literacy rate and mean years of schooling. The decent standard of living dimension was represented by per-capita expenditure. All of these variables are derived from the National Socio-Economic Survey.

In 2014, BPS-Statistics of Indonesia revised the methodology of the HDI. The following changes were implemented:

1. The literacy rate indicator was replaced by an indicator of the expected years of schooling. The reason behind this change is that many districts across Indonesia have already achieved high levels of literacy.
2. The population coverage to compute the mean years of schooling was changed from population aged 15 and above to population aged 25 and above.
3. Due to changes in consumption patterns, the number of commodities used to calculate expenditure per capita was changed from 26 to 96.
4. To improve measurement precision, the mean computation of the HDI was changed from arithmetic to geometric.

To carry out a spatial analysis, a spatial weights matrix **W** is needed to summarize the spatial structure of the data. In this matrix, non-zero values of w_{ij} represent a "neighbor" relationship in a geographical sense. There are several ways to specify the matrix **W**. Among the most common specifications, there is the simple contiguity structure in which two regions are defined as neighbors when they share a common border and/or a vertex. Other specifications can include distance thresholds, inverse distance, and k-nearest neighbors.

As indicated by Vidyattama (2014), Indonesia has unique geographical landscape and given the number of separated islands that form the archipelago, the notion of geographic distance is usually selected as the first criteria to build a spatial weights matrix. Thus, based on the geographic centroids of each district as reference points, the present paper uses an inverse distance criteria to define the spatial weights matrix of Indonesia.

Figure 1 and 2 provide a first overview of the data and main variable used in this paper. The range of HDI is from 0 (minimum score) to 100 (maximum score). According to the Central Statistics Bureau of Indonesia, districts are categorized as having a very high level human development if their HDI score reaches a minimum of 80. In contrast, districts with HDI score less than 60 are classified as low development regions.[6]

Fig. 1: Human development index across districts in Indonesia in 2010

Figure 1 and 2 show patterns of improvement in human development across districts in Indonesia. On the one hand, the number of low HDI districts has reduced from 121 in 2010 to 26 in 2018. On the other, the number of high HDI districts has increased significantly from 3 in 2010 to 29 in 2018. Both maps also indicate that these regional dynamics have a geographical component. From a simple observation, it appears that, in the west (east) side, some regions of high (low) HDI tend to be surrounded by other regions

[6] See Appendix B for further details about this classification.

Fig. 2: Human development index across districts in Indonesia in 2018

of high (low) HDI. In the next section, analyses of spatial dependence and convergence will evaluate this and related observations more formally.

4 Results

4.1 Exploratory spatial analysis and regional disparities

Historically, Indonesia has been characterized by large regional disparities in various economic and social dimensions. Over the recent 2010-2018 period, however, disparities in many social indicators have been decreasing. Figure 3 shows the evolution of regional disparities based on the standard deviation of the log of the human development index and its components. Based on the values of the right axis of each sub-figure, it is clear that disparities across districts in the human development index, and most of its components, have been systematically decreasing. The only exception is expenditure per capita, which shows a clear increasing trend (Figure 3 e).

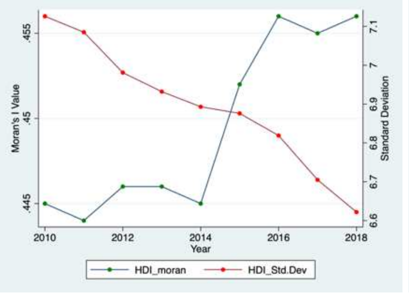
Figure 3 also shows clear trends of global spatial dependence. Spatial dependence is measured based on the value of a global indicator of spatial autocorrelation, which in this case is the Moran's I indicator. The values of the left axis of each sub-figure indicate that spatial dependence has been increasing over the 2010-2018 period for all variables. A common interpretation of increasing spatial dependence is that regions are responding in a more similar fashion to economic and social changes. Moreover, as regions develop, they tend to interact more with other proximate regions (Magalhães and Hewings 2005).

The patterns of Figure 3 highlight an important and appealing relationship: increasing patterns of spatial dependence tend to be associated with decreasing regional disparities, at least in terms of social development variables. In the next subsection, we evaluate this relationship in the context of a spatial convergence framework. Before diving into that evaluation, however, let us review some local patterns of spatial dependence, which are also useful for understanding the diffusion of spatial spillover effects and the reduction of regional disparities.

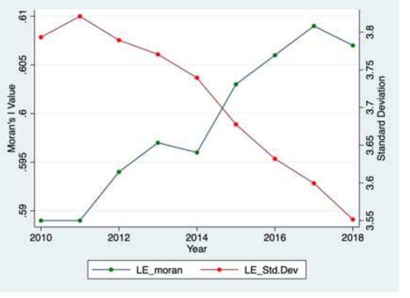
The analysis of local spatial dependence suggested by Anselin (1995) is useful for identifying the location of spatial clusters and spatial outliers. Figures 4 and 5 highlight the spatial distribution of regional disparities based on the location of spatial clusters. Hot spots (clusters of high values surrounded by other high values) are located in the western area of Indonesia, while cold spots (clusters of low values surrounded by other low values) are located in the east. This east-west dichotomy has been a persistent feature of the Indonesian economy. Although regional disparities in human development have been decreasing over time (Figure 3a), the east-west dichotomy is still present in 2018 (Figure 5).

Hot spots and cold spots are clusters of regions in which spatial dependence is both high and statistically significant. As such, if there is shock in any region belonging to these clusters, a high degree of spatial dependence would facilitate the diffusion and amplification of the shock to the neighbors of that region. As the number of regions defined as hot spots is more than two times larger than the number of cold spots, improvements in human development may have diffused to more regions in the west. Thus, the reduction in regional disparities indicated by Figure 3a may be dominated by the progress of western regions.

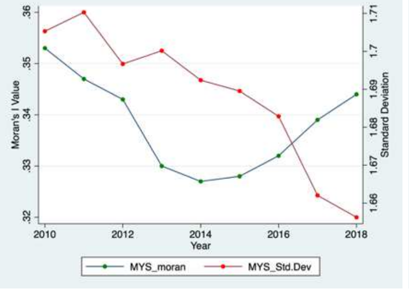
Spatial outliers may also play a role in the process of reduction of regional disparities. It is worth noticing that the number of spatial outliers is relative high in both years, 91 in 2010 and 88 in 2018. Moreover, most spatial outliers are located in the west side of the country, 81 in 2010 and 79 in 2018. Thus, western regions with relatively low human development could potentially benefit from the progress of their surrounding neighbors, which are characterized by relatively high human development.



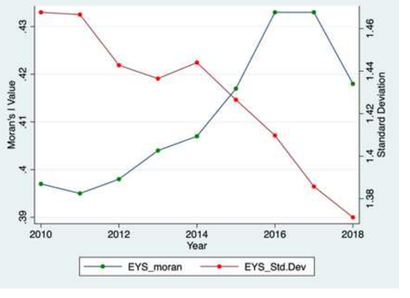
(a) Human development index (HDI)



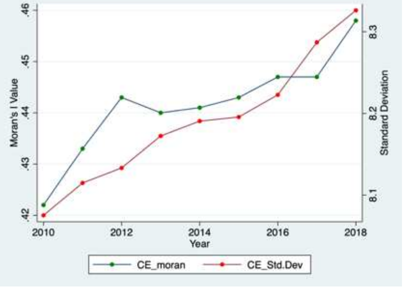
(b) Life expectancy (LE)



(c) Expected years of schooling (EYS)



(d) Mean years of schooling (MYS)



(e) Expenditure per capita (EXP)

Fig. 3: Evolution of regional disparities and global spatial dependence 2010-2018

Notes: Regional disparities (right axis) are measured based on the standard deviation of the log of each variable. Global dependence (left axis) is measured based on the Moran's I, which is statistically significant at 5% level for all years.

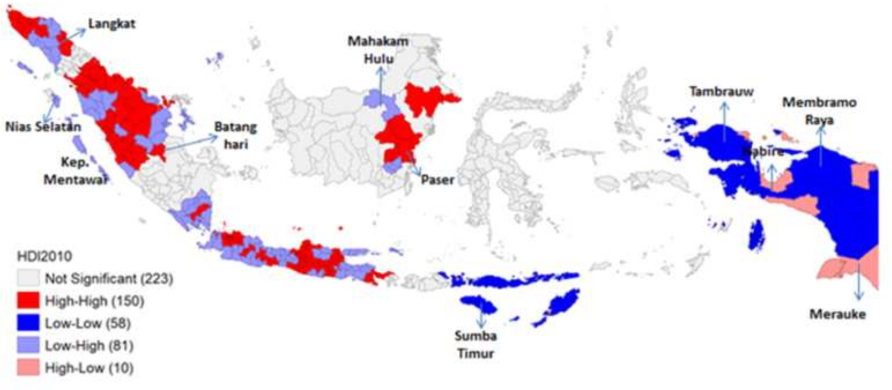


Fig. 4: Human development disparities in Indonesia: Hot spots and cold spots of local dependence in 2010

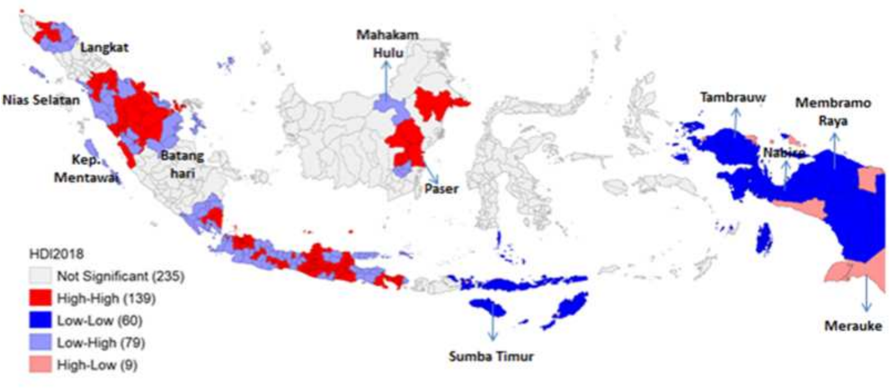


Fig. 5: Human development disparities in Indonesia: Hot spots and cold spots of local dependence in 2018

4.2 Regional convergence and spatial effects

This section presents the main results of the convergence models described in Section 3.2. Table 1 presents the results of non-spatial convergence analysis of the human development index and its components. It also presents the results of a test of spatial dependence in the residuals.

The convergence coefficients reported in Table 1 are all negative and statistically significant. These coefficients indicate that relatively underdeveloped districts have been growing faster than relatively developed districts in In-

Table 1: Regional convergence and spatial dependence test

	(1) HDI growth 2010-2018	(2) LE growth 2010-2018	(3) EYS growth 2010-2018	(4) MYS growth 2010-2018	(5) EXP growth 2010-2018
Log of HDI in 2010	-0.179***				
	(0.019)				
Log of LE in 2010		-0.104***			
		(0.009)			
Log of EYS in 2010			-0.301***		
			(0.017)		
Log of MYS in 2010				-0.234***	
				(0.024)	
Log of EXP in 2010					-0.071***
					(0.010)
Constant	0.821***	0.450***	0.860***	0.588***	0.799***
	(0.078)	(0.036)	(0.040)	(0.048)	(0.088)
Observations	514	514	514	514	514
R-squared	0.697	0.204	0.687	0.668	0.111
Convergence indicators					
Convergence speed	0.025	0.014	0.045	0.033	0.009
Half-life in years	28.07	50.71	15.48	20.85	75.51
Test of spatial dependence in the residuals					
Moran's I test	31.15	24.54	1.88	2.42	58.81
P-value	0.00	0.00	0.17	0.12	0.00

Note: HDI stands for human development index, LE stands for life expectancy, EYS stands for expected years of schooling, MYS stands for mean years of schooling, EXP stands for expenditure per capita.
Robust standard errors in parentheses.
$***p < 0.01, **p < 0.05, *p < 0.1$

donesia. Thus, a process of regional convergence is taking place in terms of the human development index and all its components.

The speed of convergence of the human development index is 2.5 percent per year. At this speed, regional disparities are expected to be halved in about 28 years. Nevertheless, there are considerable differences in the speed of convergence across the components of the human development index. For instance, the component of the expected years of schooling shows the fastest convergence speed at 4.5 percent per year, while the component of expenditure per capita shows the slowest convergence speed at 0.9 percent per year. Small differences in the speed of convergence have large implications in terms of the time that is needed to reduce regional disparities. For instance, reducing disparities by half in expenditure per capita would take almost five times longer (75.51 years) than in expected years of schooling (15.48 years).

From a compositional standpoint, the speed of convergence of the human development index is determined by the speed of convergence of its components. On the one hand, regional convergence in expected years of schooling and mean years of schooling have tended to accelerate the speed of convergence of human development. On the other hand, the slow speed of convergence of expenditure per capita and life expectancy have tended to decelerate it.

Table 2: Spatial convergence models for the human development index

Dependent variable: HDI growth 2010-2018			
	(1) OLS	(2) SLM	(3) SEM
Log of HDI in 1990	-0.179***	-0.190***	-0.193***
	(0.019)	(0.005)	(0.006)
Spatial lag coefficient		0.406***	
		(0.073)	
Spatial error coefficient			2.632***
			(0.152)
Constant	0.821***	0.854***	0.870***
	(0.078)	(0.028)	(0.023)
Convergence indicators			
Convergence speed	0.025	0.026	0.027
Half-life in years	28.07	26.32	25.86
Model selection/information criteria			
AIC	-2867.782	-2893.582	-2915.181
BIC	-2859.298	-2876.614	-2898.212

Notes: Robust standard errors in parentheses.
$***p < 0.01, **p < 0.05, *p < 0.1$

The bottom of Table 1 evaluates the hypothesis that the residuals of the convergence regressions are independent and identically distributed. Results indicate that the human development index, life expectancy, and the expenditure per capita show statistically significant patterns of (residual) spatial dependence. As such, the econometric convergence model for each of these variables is not only misspecified, but could suffer from an omitted spatial variable bias. To handle these concerns, it is necessary to formally include the role of spatial dependence in the estimation of convergence coefficients for each of these three variables.

Tables 2 to 5 show how accounting for spatial dependence affects the speed of regional convergence of human development, life expectancy, and expenditure per capita. All spatial regressions are estimated using the maximum likelihood estimator for cross-sectional data. Table 2 evaluates the role of spatial dependence in the convergence equation of the human development index. For reference purposes, the first column restates the non-spatial convergence model, which was estimated in Table 1 using the ordinary least squares (OLS) estimator. The second column shows the results of the spatial lag model (SLM). The spatial lag coefficient is positive and statistically significant. In a convergence framework, this model indicates that the growth rates of the neighbors of a region directly affect its growth rate. The third column shows the results of the spatial error model (SEM). The spatial term of this model is also positive and statistically significant. Conceptually, this model indicates that the regression residuals of a region are related to the regression residuals of neighboring regions. The model selection criteria at the bottom of Table 2 indicates that the spatial error model is more suitable for evaluating regional convergence in the human development index. According to this specification, spatial dependence tends to increase the speed of regional convergence from 2.5 percent to 2.7 percent.

Table 3 evaluates the role of spatial dependence in the life expectancy component. Similarly to the human capital index, the spatial lag model (SLM) are spatial error model (SEM) are statistically significant. However, the spatial lag model has the lowest AIC and BIC. Therefore, this model is the most suitable for evaluating regional convergence in life expectancy. According to this specification, spatial dependence tends to increase the speed of regional convergence.

Table 4 evaluates the role of spatial dependence in expenditure per capita. Similarly to the human development index, the spatial lag model (SLM) and spatial error model (SEM) are statistically significant. In contrast to the human development index, the model selection criteria (lowest AIC and BIC) indicates that the spatial lag model is more suitable for evaluating regional convergence in expenditure per capita. According to this specification, spatial dependence appears to increase the speed of regional convergence.

For life expectancy as well as expenditure per capita, the spatial lag model (SLM) appears to be the most suitable econometric specification. As argued by LeSage and Pace (2009), the estimated coefficient of a SLM specification can be decomposed into direct and indirect effects, where the latter indicates the contribution of spatial spillovers. Table 5 presents the results of this decomposition for both variables. In the case of life expectancy, the indirect ef-

Table 3: Spatial convergence models for life expectancy

Dependent variable: LE growth 2010-2018			
	(1) OLS	(2) SLM	(3) SEM
Log of LE in 1990	-0.104***	-0.132***	-0.113***
	(0.009)	(0.009)	(0.009)
Spatial lag coefficient		2.754***	
		(0.239)	
Spatial error coefficient			0.910***
			(0.089)
Constant	0.450***	0.561***	0.489***
	(0.037)	(0.038)	(0.041)
Convergence indicators			
Convergence speed	0.014	0.018	0.015
Half-life in years	50.71	39.17	46.24
Model selection/information criteria			
AIC	-3118.62	-3144.72	-3131.28
BIC	-3110.14	-3127.75	-3114.31

Notes: Robust standard errors in parentheses.
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 4: Spatial convergence models for expenditure per capita

Dependent variable: EXP growth 2010-2018			
	(1) OLS	(2) SLM	(3) SEM
Log of EXP in 1990	-0.0708***	-0.0968***	-0.0808***
	(0.001)	(0.009)	(0.009)
Spatial lag coefficient		0.770***	
		(0.099)	
Spatial error coefficient			0.943***
			(0.057)
Constant	0.799***	0.991***	0.883***
	(0.088)	(0.079)	(0.082)
Convergence indicators			
Convergence speed	0.009	0.013	0.011
Half-life in years	75.52	54.47	65.82
Model selection/information criteria			
AIC	-1510.84	-1557.14	-1535.15
BIC	-1502.36	-1540.17	-1518.18

Notes: Robust standard errors in parentheses.
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 5: Direct and indirect effects

	(1) LE growth 2010-2018	(2) EXP growth 2010-2018
Direct effect		
Log of LE in 1990	-0.131***	
	(0.009)	
Log of EXP in 1990		-0.097***
		(0.009)
Convergence indicators of direct effect		
Convergence speed	0.018	0.013
Half-life in years	39.49	54.35
Indirect effect		
Log of LE in 1990	0.635	
	(0.439)	
Log of EXP in 1990		-0.038***
		(0.009)
Convergence indicators of indirect effect		
Convergence speed	na	0.005
Half-life in years	na	143.14
Total effect		
Log of LE in 1990	0.504	
	(0.442)	
Log of EXP in 1990		-0.134***
		(0.017)
Convergence indicators of total effect		
Convergence speed	na	0.018
Half-life in years	na	39.39

Notes: LE stands for life expectancy and EXP stands for expenditure per capita.
Robust standard errors in parentheses.
$***p < 0.01, **p < 0.05, *p < 0.1$

fect turns out to be not statistically significant and convergence indicators are not calculated. In the case of expenditure per capita, the indirect effect is statistically significant. Moreover, spatial spillovers accelerate the speed of convergence from 1.3 percent to 1.8 percent per year. This seemingly small difference has important convergence implications. Without spatial spillovers, disparities in expenditure per capita would be reduced by half after 54 years. With spatial spillovers, however, those disparities would be reduced in 39 years.

5 Concluding remarks

This paper evaluates the evolution of regional disparities in human development index across 514 districts in Indonesia over the 2010-2018 period. Overall, we find decreasing trend in regional disparities over time. Moreover, regions with initially low human development in 2010 have been growing faster than those with initially high human development. This process of regional convergence occurs not only in the human development index, but also almost in its entire components: life expectancy, expected years of schooling, mean years of schooling, except expenditure per capita.

The evolution of regional disparities as well as the process of regional convergence are highly related to the degree of spatial dependence across Indonesian districts. Indeed, the main result of this paper highlights that increasing spatial dependence is associated with decreasing regional disparities and faster regional convergence. Nevertheless, an analysis of local spatial dependence suggests that in spite of the reduction in regional inequality, the development gap between the east and west of Indonesia is still persistent.

The speed of regional convergence in human development depends on the convergence speed of its four components. On the one hand, faster convergence in expected years of schooling and mean years of schooling tend to accelerate the speed of convergence of human development. On the other hand, the slow speed of convergence of expenditure per capita and life expectancy tends to decelerate it.

An econometric analysis of regional convergence reveals that the human development index, life expectancy, and the expenditure per capita are characterized by statistically significant patterns of spatial dependence in the regression residuals. As such, the modelling of regional convergence needs to be adjusted to include the role of spatial dependence. For modeling the convergence dynamics of the human development index, a spatial error model (SEM) specification appears to be the most appropriate model. Under this specification, spatial dependence increases the speed of regional convergence increases from 2.5 to 2.7 percent per year. For modeling the convergence dynamics of life expectancy and expenditure per capita, a spatial lag model (SLM) specification appears to be the most appropriate. Under this specification, spatial dependence increases the speed of convergence in both variables. In particular, for expenditure per capita, statistically significant spatial spillovers increase the speed of convergence from 1.3 to 1.8 percent per year.

This is a considerable effect relative to previous estimates in the literature. It implies that more than 25 percent of the convergence rate in expenditure per capita is explained by spatial spillovers.

From a policy standpoint, the findings of this paper can provide some guidance in design of regional development policies in two fronts. First, to increase the speed of regional convergence in human development, disparities in life expectancy and expenditure per capita need to be reduced at a higher speed. Second, as spatial dependence plays an important role in both the location of regional disparities and the convergence of human development, local governments are urged to spatially coordinate their development plans.

Finally, this paper has only evaluated regional disparities using classical methods of spatial dependence and convergence. Although these methods are intuitive and parsimonious, further research seems promising in at least three fronts. First, when longer time series become available, spatial panel data models could be implemented to control for unobserved heterogeneity. Second, additional spatial specifications can be tested. Following the approach of LeSage and Pace (2009), the first specification could be the Spatial Durbin Model and, based on restrictions to the regression coefficients, the SLM and SEM specifications can be derived and tested. Third, in addition to spatial dependence, the role of spatial heterogeneity in the convergence process can be evaluated using a geographically weighted regression (Eckey et al 2007).

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Appendix

Appendix A: Districts with Lowest Level of Human Development Index in Indonesia, 2018

Number	District	HDI	Number	District	HDI
1	Pulau Taliabu	59.67	14	Mamberamo Raya	51.24
2	Malaka	59.66	15	Deiyai	49.55
3	Manggarai Timur	59.49	16	Asmat	49.37
4	Teluk Wondama	58.86	17	Tolikara	48.85
5	Manokwari Selatan	58.84	18	Yahukimo	48.51
6	Maybrat	58.16	19	Puncak Jaya	47.39
7	Mappi	57.72	20	Lanny jaya	47.34
8	Jayawijaya	56.82	21	Yalimo	47.13
9	Paniai	55.83	22	Intan Jaya	46.55
10	Sabu Raijua	55.79	23	Memberamo Tengah	46.41
11	Pegunungan Arfak	55.31	24	Pegunungan Bintang	44.22
12	Dogiyai	54.44	25	Puncak	41.81
13	Tambrauw	51.95	26	Nduga	29.42

Notes: Data from the BPS-Statistics of Indonesia.

Appendix B: Categories of Regions Based on the Human Development Index of Indonesia, 2018

Level of HDI	Districts	HDI Range
Very high	Jakarta (capital city of the country), Yogyakarta, Sleman, Denpasar, Padang, Banda Aceh, Salatiga, Kendari	80
High	Medan, Pekanbaru, Dumai, Jambi, Palembang, Batam, Magelang, Purworejo, Mataram, Balikpapan, Ternate, Gorontalo, Palopo, Samarinda, Kota Sorong, Jayapura, Gorontalo	70 HDI <80
Medium	Simelue, Aceh Singkil, Langkat, Kep. Anambas, Lingga, Mukomuko, Mandailing Natal, Tapsel, Garut, Cianjur, Tasikmalaya, Kapuas, Kutai Barat, Bombana, Enrekang Karangasem, Buleleng, Sumba Barat, Nabire, Sikka, Barito Selatan, Utara, Ende, Teluk Bintuni, Manokwari	60 HDI <70
Low	Sampang, Mentawai, Nias, Timor Tengah Selatan, Sumba Barat Daya, Rote Nda, Belu, Alor, Maluku	<60

Notes: Districts that displayed on the table above are only a selected sample that represent each category

Appendix C: Calculation of HDI and Each Component in Indonesia

Health Dimension (Life Expectancy at Birth/LE)

$$I_{\text{health}} = \frac{LE\text{of region } X - \text{Minimum } LE}{\text{Maximum LE} - \text{Minimum LE}}$$

Mean Years of Schooling (MYS)

$$I_{MYS} = \frac{MYS \text{ of region } X - \text{Minimum MYS}}{\text{Maximum MYS - Minimum MYS}}$$

Expected Years of Schooling (EYS)

$$I_{EYS} = \frac{EYS \text{ of region } X - \text{Minimum EYS}}{\text{Maximum EYS - Minimum EYS}}$$

Education Indicator

$$I_{\text{education}} = \frac{I_{EYS} + I_{MYS}}{2}$$

Decent Standard of Living Dimension (Expenditure per Capita/CE)

$$I_{\text{expenditure}} = \frac{CE \text{ of region } X - \text{Minimum } CE}{\text{Maximum } CE - \text{Minimum } CE}$$

The score of HDI can be formulated as geometric mean of those three dimensions, as follows:

$$HDI = \sqrt[3]{I_{\text{health}} \times I_{\text{education}} \times I_{\text{expenditure}}} \times 100$$

Source: *www.bps.go.id*, BPS-Statistics of Indonesia